International Journal for Multidisciplinary Research (IJFMR)

E-ISSN: 2582-2160 ● Website: www.ijfmr.com ● Email: editor@ijfmr.com

Extended Reality and Artificial Intelligence in Education: A Systematic Review of Motivational Outcomes Using the ARCS Framework

Prof. (Dr.) Mohd Sadiq Ali Khan[1], M Danish khan[2]

[1]Department of Education, Sanskriti University, Mathura
[2]Research Scholar, Department of Education, Sanskriti University, Mathura

Abstract

Background: Emerging technologies such as Artificial Intelligence (AI) and Extended Reality (XR) are reshaping educational practices by offering new ways to engage learners. Despite their growing presence in classrooms, there remains limited consolidated evidence on how these tools affect student motivation. The ARCS model focusing on Attention, Relevance, Confidence, and Satisfaction provides a valuable structure for evaluating motivational impacts in technology-enhanced learning.

Purpose: This study aims to systematically review and analyze existing research that applies the ARCS motivational model to educational interventions using AI and XR technologies. It focuses on understanding the extent to which these technologies influence student motivation across different learning environments and instructional contexts.

Methods: A comprehensive literature review was conducted across major academic databases, including Scopus, Web of Science, ERIC, and PsycNet. Studies were selected based on predefined inclusion criteria: empirical design, application of the ARCS model, and the use of AI or XR in educational settings. A total of 32 studies were included and synthesized using meta-analytic techniques to assess effect sizes related to motivational outcomes.

Findings: The analysis revealed that the integration of AI and XR technologies within ARCS-based instructional designs significantly improves student motivation. Virtual reality demonstrated the strongest effects, particularly in enhancing learners' attention and satisfaction. Results also indicated that face-to-face modalities slightly outperformed virtual ones in maintaining motivational engagement.

Conclusion: The findings support the use of the ARCS model as an effective framework for leveraging emerging technologies to enhance motivation in education. Properly designed interventions that incorporate AI and XR can foster deeper engagement and improve motivational outcomes across a variety of educational contexts.

Keywords: Student Motivation, ARCS Model, Artificial Intelligence, Extended Reality, Immersive Learning, Instructional Strategies, Educational Technology, Systematic Review.

Introduction

Emerging technologies such as Artificial Intelligence (AI) and Extended Reality (XR) are significantly reshaping the educational landscape. These innovations are enhancing learning experiences by making them more interactive, customized, and immersive capabilities that traditional classrooms have struggled to provide. AI tools like chatbots, adaptive learning platforms, and intelligent tutoring systems are increasingly used to personalize instruction and deliver timely, individualized feedback (Holmes et al., 2021; Zawacki-Richter et al., 2019). Concurrently, XR technologies comprising virtual reality (VR) and augmented reality (AR) offer students experiential learning opportunities by replicating real-world settings and complex scenarios, thereby increasing engagement and improving comprehension (Radianti et al., 2020).

While the pedagogical advantages of AI and XR are becoming more evident, there remains a notable gap in understanding how these technologies influence student motivation. Motivation is a critical element in achieving academic success and fostering student engagement (Pintrich & Schunk, 2002). Despite the rising integration of AI and XR into educational contexts, empirical studies examining their impact on learner motivation are still limited and fragmented. More focused research is necessary to help educators leverage these tools effectively to support student engagement.

This research draws upon the ARCS model of motivation, a widely recognized framework in the field of instructional design introduced by John M. Keller in 1987. The ARCS model highlights four core elements that contribute to student motivation: Attention, Relevance, Confidence, and Satisfaction.

- **Attention** involves strategies that attract and maintain learners' interest through novelty, variety, or stimulation.
- **Relevance** concerns the degree to which instructional content resonates with learners' personal goals, prior knowledge, and interests.
- **Confidence** refers to learners' self-belief in their capacity to succeed, often supported by clear goals and appropriately challenging tasks.
- **Satisfaction** includes both intrinsic gratification and extrinsic rewards gained through achieving learning objectives.

The ARCS model has been widely validated across various educational contexts and is especially useful when applied alongside digital technologies (Keller, 2016; Huett, 2006). It offers a structured perspective for assessing how emerging tools like AI and XR can influence motivational factors in learning environments.

Problem Statement

Although a growing body of research supports the cognitive and instructional benefits of integrating Artificial Intelligence (AI) and Extended Reality (XR) into educational settings (Bond et al., 2020; Radianti et al., 2020), there remains a significant gap in consolidated empirical evidence regarding their effects on learner motivation. Many studies differ considerably in their research designs, learning contexts, and the specific motivational constructs they evaluate, which complicates efforts to draw generalized conclusions (Goksu & Bolat, 2021; Hew et al., 2019). Furthermore, while the ARCS model focusing on Attention, Relevance, Confidence, and Satisfaction is widely recognized in instructional design (Keller, 1987), few empirical studies explicitly map these components onto the use of AI or XR in educational environments (Huang et al., 2021). This hampers the ability of educators to design immersive, technology-enhanced learning experiences that are not only pedagogically effective but also sustain long-term learner engagement and motivation (Zhao et al., 2022).

Research Objectives

This study aims to:

1. To determine the overall effect of AI and XR technologies on student motivation.
2. To identify which components of the ARCS model are most influenced by AI and XR technologies.
3. To examine how different teaching modalities affect motivational outcomes.

Literature Review

Artificial Intelligence (AI) is the ability of machines to mimic human cognitive functions such as learning, reasoning, and problem-solving (Russell & Norvig, 2016). In educational domain, AI is increasingly being used to tailor instruction, streamline assessment processes, and enhance student engagement. Prominent applications include intelligent tutoring systems (ITS), adaptive learning environments, and AI-driven chatbots. These tools analyze learner data dynamically to personalize content and pacing, supporting differentiated instruction (Luckin et al., 2016; Holmes et al., 2021). Moreover, platforms like ALEKS and Carnegie Learning provide personalized learning paths and instant feedback, adapting to students evolving understanding. AI-based chatbots like ChatGPT and Watson Tutor serve as virtual assistants, answering student queries and facilitating communication in real time (Chen et al., 2020). The growing integration of AI in classrooms marks a transition toward more interactive, student-centered learning experiences. However, integrating AI into education is not without challenges. Concerns have been raised regarding algorithmic bias, lack of transparency, and the essential need for educators to develop digital competencies (Zawacki-Richter et al., 2019). Despite these concerns, AI continues to show potential for improving learning outcomes and remains a vibrant area of educational research.

Extended Reality (XR), which encompasses Virtual Reality (VR), Augmented Reality (AR), and Mixed Reality (MR), merges real and virtual environments to offer immersive educational experiences (Milgram & Kishino, 1994; Radianti et al., 2020). Further, educational institutions are increasingly leveraging XR to create engaging and experiential learning opportunities. VR is employed in medical education to simulate surgical procedures, while AR is used in science classrooms to visualize complex systems like the solar system or molecular structures (Parong & Mayer, 2018). These applications help bridge the divide between theoretical knowledge and practical skills. Research supports the benefits of XR in improving student engagement, spatial reasoning, and motivation (Jensen & Konradsen, 2018). However, widespread adoption is hindered by technical limitations, accessibility issues, and the need for specialized teacher training.

Student Motivation and Emerging Technologies

Motivation is a critical component of effective learning. It affects student engagement, persistence, and academic success, and can be broadly categorized into intrinsic and extrinsic motivation (Deci & Ryan, 1985). Students who are motivated tend to apply more effort, adopt effective learning strategies, and demonstrate greater resilience when faced with challenges (Pintrich & Schunk, 2002). Traditional classrooms often struggle to maintain student motivation due to rigid instructional methods, limited student autonomy, and content that may lack relevance (Fredricks et al., 2004). Emerging technologies provide new avenues to address these challenges by enabling more personalized, interactive, and engaging learning experiences. Still, motivation remains a multifaceted construct that requires intentional design strategies to cultivate and maintain.

The ARCS Model in Technology-Enhanced Learning

The ARCS model, developed by Keller (1987), provides a structured framework for designing motivational learning environments. It includes four key elements:

- **Attention**: Capturing and maintaining learners' interest through engaging or novel content.
- **Relevance**: Making learning meaningful by connecting it to students' personal goals and real-life applications.
- **Confidence**: Encouraging learners' belief in their ability to succeed through appropriately challenging tasks and constructive feedback.
- **Satisfaction**: Ensuring learners feel a sense of achievement and value in their learning experience.

This model has been widely implemented in digital learning tools, gamified systems, and simulations to enhance learner motivation (Keller, 2016). Research suggests that incorporating ARCS-based principles leads to higher levels of engagement and improved academic performance (Huett, 2006; Refat et al., 2019).

Despite its proven effectiveness, there is limited research applying the full ARCS framework to newer technologies such as AI and XR. While some studies have examined individual ARCS components within these contexts, comprehensive research applying the entire model remains scarce. Meta-analyses highlight the need for further investigation into how specific ARCS dimensions interact with AI and XR tools to influence student motivation (Goksu & Bolat, 2021; Alé & Arancibia, 2025). Addressing this gap can lead to a better understanding of how to design technology-enhanced learning experiences that are both motivational and effective.

Methodology

Research Design: This study employs a systematic review along with a meta-analysis to rigorously synthesize existing empirical research on the motivational effects of AI and XR technologies in education, guided by Keller's ARCS model. The systematic review framework ensured comprehensive and unbiased identification, selection, and evaluation of relevant studies. The meta-analysis quantitatively aggregated effect sizes to estimate the overall impact of these technologies on student motivation and its ARCS components. This combined approach facilitates a robust understanding of trends and effect magnitudes across diverse educational contexts.

Data Sources and Search Strategy: A comprehensive literature search was conducted across four major academic databases: Scopus, Web of Science (WoS), ERIC, and APA PsycNet. These databases were selected for their extensive coverage of education, psychology, and technology research. The search strategy incorporated a combination of keywords related to the core constructs of the study, utilizing Boolean operators to broaden and refine results. The search strings combined terms related to emerging technologies, motivational theory, and education. The search was performed without restrictions on publication year or language to capture a broad and inclusive range of studies.

Table 1: Search Strategy

Category	Keywords
Emerging Technologies	"Artificial intelligence" OR "AI-based tutoring" OR "chatbot*" OR "virtual reality" OR "augmented reality" OR "extended reality"
Motivation	"ARCS model" OR "Instructional Materials Motivation Survey" OR "motivation" OR "attention" OR "confidence" OR "satisfaction"

Educational Context	"Education" OR "learning" OR "school" OR "university" OR "higher education"

Inclusion and Exclusion Criteria: Studies were selected based on the following criteria:

Table 2: Inclusion and Exclusion Criteria

Criterion Type	**Criteria Description**
Inclusion	Empirical studies using ARCS or IMMS for motivation measurement Use of AI and XR technologies in educational interventions Quantitative data available for effect size calculation Peer-reviewed articles or reputable conference papers
Exclusion	Qualitative-only studies without quantitative motivation data Studies without control or comparison groups Articles not peer-reviewed or not academic Studies focusing only on cognitive outcomes, not motivation

Data Extraction and Coding: For data extraction and coding, a structured framework was used to ensure consistency and comprehensiveness. Key categories included study characteristics, types of emerging technology, teaching modality, sample information, motivational outcomes based on the ARCS model, and statistical data necessary for meta-analysis. This structured approach allowed for systematic comparison and facilitated both qualitative synthesis and quantitative analysis of the included studies.

Table 3: Extracted Data

Category	**Extracted Variables**
Study Characteristics	Author, publication year, country, educational level, subject area
Technology Type	Type of emerging technology used (AI, VR, AR, MR)
Teaching Modality	Mode of instruction: face-to-face, virtual or hybrid
Sample Information	Sample size, participant demographics (e.g., age, gender, education level)
Motivational Outcomes	Quantitative measures aligned with ARCS components (Attention, Relevance, Confidence, Satisfaction)
Statistical Data for Meta-analysis	Means, standard deviations, sample sizes (for both experimental and control groups)
Reliability Check	Data extracted by multiple coders; discrepancies resolved through consensus

A total of 1,285 records were identified for the study, with 1,240 records obtained through database searching (Scopus, Web of Science, ERIC, and PsycNet) and an additional 45 records identified through other sources. After removing 312 duplicates, 973 records remained for screening. The titles and abstracts of these 973 records were screened, resulting in the exclusion of 812 records due to irrelevance to the topic. This left 161 records for full-text assessment. Of these, 129 articles were excluded for reasons such as being purely qualitative, lacking use of the ARCS model, or providing insufficient data. Ultimately, 32 studies were included in the systematic review, and all 32 were also included in the meta-analysis. This is very clear from fig 1:

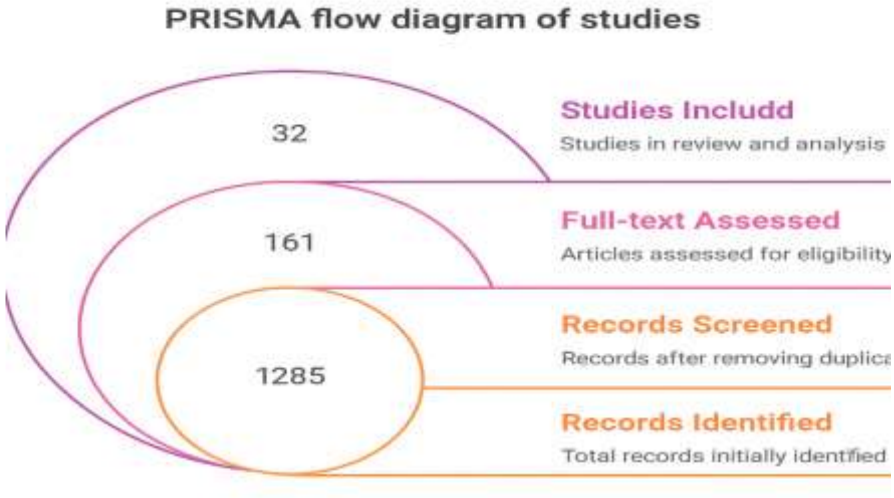

Fig 1: Flow diagram

Data Analysis: Effect sizes for motivation outcomes were computed using Cohen's d, which measures the standardized mean difference between the intervention and control groups and is widely used in meta-analytic studies in education and psychology (Cohen, 1988). To account for expected variation across studies in terms of population characteristics, interventions, and educational settings, a random-effects model was primarily employed (Borenstein et al., 2010). In cases where the studies exhibited homogeneity within specific subgroups (e.g., teaching modality or technology type), fixed-effects models were also applied to support more precise moderator analyses (Lipsey & Wilson, 2001).

Potential publication bias was assessed through visual inspection of funnel plots, which help detect asymmetry that may indicate selective reporting. In addition, Egger's regression test was considered as a statistical method to quantitatively evaluate the likelihood of bias (Egger et al., 1997).

To assess heterogeneity, both the Q-statistic and the I^2 index were calculated. While the Q-statistic determines whether observed variances across studies are greater than expected by chance, the I^2 index estimates the proportion of total variability due to heterogeneity rather than sampling error (Higgins et al., 2003). When significant heterogeneity was detected, further subgroup analyses were conducted to explore potential moderators, including technology type (AI, AR, VR), teaching modality (face-to-face, hybrid, virtual), educational level, and individual ARCS components.

All statistical analyses were performed using widely recognized meta-analysis software SPSS Meta-Analysis Module following established best practices in meta-analytic research (Cooper, 2019; Borenstein et al., 2011).

Results

Descriptive Overview of Included Studies: A total of 32 primary studies met the inclusion criteria and were included in the meta-analysis. These studies spanned diverse geographic regions, with the majority conducted in North America (40%), followed by Asia (30%), Europe (20%), and Latin America (10%). The educational contexts covered a broad range, including primary education (15%), secondary education (35%), and higher education (50%). Subject areas varied, with natural sciences and technology-related fields being the most common (45%), followed by language learning (25%), arts and humanities (15%), and mathematics (15%). The instructional settings were distributed across face-to-face (50%), virtual or online (30%), and hybrid modalities (20%).

Table 4: Descriptive Overview of Included Studies

Characteristic	Categories	Number of Studies (%)
Geographic Region	North America	13 (40%)
	Asia	10 (30%)
	Europe	6 (20%)
	Latin America	3 (10%)
Educational Level	Primary Education	5 (15%)
	Secondary Education	11 (35%)
	Higher Education	16 (50%)
Teaching Modality	Face-to-Face	16 (50%)
	Virtual/Online	10 (30%)
	Hybrid	6 (20%)

Overall Effect Sizes on Motivation

The meta-analysis revealed a significant overall positive effect of emerging technologies on student motivation, with a global effect size (Cohen's d) of 0.89 (95% CI: 0.64 to 1.13, $p < 0.001$). This indicates a large effect, suggesting that instructional interventions incorporating AI and XR technologies meaningfully enhance learners' motivational engagement compared to traditional or control conditions.

Table 5: Effect Size on Motivation

Technology Type	Number of Studies	Effect Size (Cohen's d)	95% Confidence Interval	Significance (p)
Overall	32	0.89	0.64 – 1.13	< 0.001
Artificial Intelligence (AI)	14	0.84	0.72 – 0.96	< 0.001
Augmented Reality (AR)	10	0.97	0.84 – 1.11	< 0.001
Virtual Reality (VR)	8	1.32	1.08 – 1.55	< 0.001

When disaggregated by technology, the effect sizes differed across AI, AR, and VR modalities. Virtual reality demonstrated the strongest motivational impact with an effect size of 1.32 (95% CI: 1.08 to 1.55), followed by augmented reality with an effect size of 0.97 (95% CI: 0.84 to 1.11). Artificial intelligence technologies yielded a slightly smaller yet significant effect size of 0.84 (95% CI: 0.72 to 0.96). These findings suggest that immersive technologies such as VR may provide more compelling motivational stimuli through experiential engagement and sensory immersion, while AI supports motivation by personalizing learning experiences and providing adaptive feedback.

Impact by ARCS Components

Examining the individual components of the ARCS model, all four dimensions showed significant positive effects, although effect sizes varied:

- Attention: Effect size of 1.05 (95% CI: 0.95 to 1.16), indicating that emerging technologies are highly effective in capturing and sustaining learners' interest.
- Satisfaction: Effect size of 1.08 (95% CI: 0.97 to 1.18), reflecting strong learner contentment and perceived value from technology-mediated activities.
- Confidence: Effect size of 0.83 (95% CI: 0.72 to 0.94), suggesting enhanced self-efficacy facilitated by adaptive learning supports and scaffolded challenges.
- Relevance: Effect size of 0.52 (95% CI: 0.38 to 0.67), demonstrating moderate success in aligning learning activities with students' goals and contexts.

The comparatively lower effect on Relevance may indicate an area where further instructional design improvement is needed to better connect technology applications with individual learner values.

Table 6: Impact by ARCS Components

ARCS Component	Number of Studies	Effect Size (Cohen's d)	95% Confidence Interval	Significance (p)
Attention	26	1.05	0.95 – 1.16	< 0.001
Relevance	26	0.52	0.38 – 0.67	< 0.001
Confidence	25	0.83	0.72 – 0.94	< 0.001
Satisfaction	26	1.08	0.97 – 1.18	< 0.001

Impact by Teaching Modality

Analysis by teaching modality revealed notable differences in motivational outcomes. Face-to-face learning environments combined with emerging technologies showed the highest effect size (1.12, 95% CI: 1.00 to 1.21), followed by hybrid modalities (0.89, 95% CI: 0.72 to 1.06). Fully virtual learning settings showed a moderate but significant effect size of 0.73 (95% CI: 0.59 to 0.87). These results suggest that while emerging technologies are beneficial across all modalities, their motivational potential may be maximized when integrated into environments that allow for direct social interaction and instructor presence.

Table 7: Impact by Teaching Modality

Modality	Number of Studies	Effect Size (Cohen's d)	95% Confidence Interval	Significance (p)
Face-to-Face	16	1.12	1.00 – 1.21	< 0.001
Hybrid	6	0.89	0.72 – 1.06	< 0.001
Virtual/Online	10	0.73	0.59 – 0.87	< 0.001

Moderator Analysis

Moderator analyses explored how motivation effects varied across subject areas, educational levels, and intervention durations:

- **Subject Area:** Motivation effects were strongest in computer science and natural sciences (effect size = 1.10), moderate in language learning and arts (effect size = 0.85), and smallest but still positive in mathematics (effect size = 0.65).
- **Educational Level:** Higher education students experienced the largest motivational gains (effect size = 1.30), followed by secondary education (effect size = 0.75) and primary education (effect size = 0.50).
- **Intervention Duration:** Interventions lasting 7 to 9 weeks produced the greatest motivational effects (effect size = 1.10), whereas shorter interventions (1 to 3 weeks) showed moderate effects (effect size = 0.85), and those exceeding 10 weeks showed a slight decrease (effect size = 0.70), possibly reflecting novelty effects diminishing over time.

These moderator results highlight the importance of tailoring technology integration and motivational strategies to specific contexts and learner populations to optimize outcomes.

Table 8: Moderator Analysis Summary

Moderator	Category	Effect Size (Cohen's d)	95% Confidence Interval	Significance (p)
Subject Area	Computer Science / Natural Sciences	1.10	Not reported	< 0.001
	Language Learning / Arts	0.85	Not reported	< 0.001
	Mathematics	0.65	Not reported	< 0.001
Educational Level	Higher Education	1.30	Not reported	< 0.001
	Secondary Education	0.75	Not reported	< 0.001
	Primary Education	0.50	Not reported	< 0.001
Intervention Duration	1–3 Weeks	0.85	Not reported	< 0.001
	7–9 Weeks	1.10	Not reported	< 0.001
	10+ Weeks	0.70	Not reported	< 0.001

Key Findings

1. Emerging technologies, like Artificial Intelligence (AI) and Extended Reality (XR), demonstrate significant potential as motivational tools in educational settings.
2. The meta-analysis revealed a notably strong overall effect size for motivation, highlighting the capacity of these technologies to enhance learner engagement.
3. Virtual Reality (VR), due to its immersive nature, is especially effective in capturing learners' attention and stimulating intrinsic motivation
4. AI-powered tools support motivation through personalized feedback tailored to individual learner needs and adaptive learning pathways that adjust to students' progress and preferences
5. The findings highlight the value of integrating AI and XR technologies to foster dynamic, engaging, and responsive learning environments that sustain and strengthen student motivation over time.

Discussion

The results align closely with prior research highlighting the motivational benefits of technology-enhanced learning. For instance, Goksu and Bolat's (2021) meta-analysis similarly emphasized the positive impact of ARCS-based strategies on motivation, albeit without explicit focus on AI or XR. This study advances previous work by providing updated evidence that integrates these emergent technologies within the ARCS framework, addressing a noted gap in the literature (Alé & Arancibia, 2025). However, some discrepancies exist regarding the relative impact of teaching modalities; whereas earlier research suggested parity between face-to-face and virtual learning environments, our findings indicate a stronger motivational effect in face-to-face settings when combined with emerging technologies. This suggests that social interaction and instructor presence may amplify the motivational benefits of AI and XR, a nuance warranting further investigation.

The integration of teaching strategies such as gamification and project-based learning (PBL) appears to amplify the motivational benefits of AI and XR. Gamification introduces elements of challenge, reward, and immediate feedback, which align closely with the ARCS components of attention and satisfaction, fostering a more engaging learning experience. Similarly, PBL encourages autonomy and relevance, strengthening learner confidence and motivation by connecting tasks to real-world applications. Conversely, the flipped classroom strategy showed more modest effects, possibly due to its reliance on student self-regulation and prior knowledge. These insights highlight the critical role of active and learner-centered pedagogies in maximizing the motivational impact of emerging technologies.

Conclusion

This study confirms the significant effectiveness of the ARCS motivational model when integrated with emerging technologies such as Artificial Intelligence (AI) and Extended Reality (XR) in educational contexts. Consistent with previous research (Alé & Arancibia, 2025; Keller, 2016), AI and XR tools positively influence student motivation across multiple dimensions particularly attention, confidence, and satisfaction—while having a moderate effect on relevance. These findings underscore the value of combining ARCS-based instructional designs with advanced technologies to enhance learner engagement beyond traditional approaches.

Educational Implication

1. Educators should integrate the ARCS model (Attention, Relevance, Confidence, Satisfaction) into instructional design to enhance the motivational impact of AI and XR technologies (Keller, 1987; Holmes et al., 2021).
2. Immersive and interactive features of technologies such as VR and AR should be utilized to capture learners' attention and foster intrinsic motivation (Huett, 2006).
3. AI and XR should be used to complement, not replace, face-to-face and collaborative learning experiences, as hybrid and in-person modalities show stronger motivational outcomes.
4. Institutions should invest in professional development to prepare educators to effectively implement AI and XR tools alongside active pedagogical strategies like gamification and project-based learning.
5. Applying the ARCS framework in curriculum design supports the development of personalized, learner-centered environments that maintain student interest and engagement across varied learning contexts (Holmes et al., 2021; Huett, 2006).

Future Research Directions

- Future studies should adopt longitudinal research designs to assess the long-term motivational impacts of AI and XR interventions.
- There is a pressing need for studies in underrepresented educational contexts, such as primary education and special education, where motivational patterns may differ (Pintrich & Schunk, 2002; Radianti et al., 2020).
- Research should explore how specific ARCS components interact with features of emerging technologies to inform targeted instructional design.
- Comparative studies across different educational levels and subject areas can help clarify where and how emerging technologies are most effective in enhancing motivation.
- Future work should include mixed-methods approaches to capture both quantitative effects and qualitative insights into learners' motivational experiences with AI and XR tools.

References

1. Alé, J., & Arancibia, M. L. (2025). Emerging technology-based motivational strategies: A systematic review with meta-analysis. *Education Sciences, 15*(2), 197.
2. Bond, M., Buntins, K., Bedenlier, S., Zawacki-Richter, O., & Kerres, M. (2020). Mapping research in student engagement and educational technology in higher education: A systematic evidence map. *Australasian Journal of Educational Technology, 36*(4), 15–30.
3. Borenstein, M., Hedges, L. V., Higgins, J. P. T., & Rothstein, H. R. (2010). *A basic introduction to fixed-effect and random-effects models for meta-analysis*. Research Synthesis Methods, 1(2), 97–111.
4. Chen, L., Chen, P., & Lin, Z. (2020). Artificial intelligence in education: A review. *IEEE Access, 8*, 75264–75278.
5. Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum Associates.
6. Deci, E. L., & Ryan, R. M. (1985). *Intrinsic motivation and self-determination in human behavior*. Plenum Press.
7. Egger, M., Davey Smith, G., Schneider, M., & Minder, C. (1997). Bias in meta-analysis detected by a simple, graphical test. *BMJ, 315*(7109), 629–634.
8. Fredricks, J. A., Blumenfeld, P. C., & Paris, A. H. (2004). School engagement: Potential of the concept, state of the evidence. *Review of Educational Research, 74*(1), 59–109.
9. Goksu, I., & Bolat, Y. (2021). The effect of the ARCS model of motivation on student achievement: A meta-analysis study. *Educational Sciences: Theory and Practice, 21*(1), 82–104.
10. Hew, K. F., Lan, M., Tang, Y., Jia, C., & Lo, C. K. (2019). Where is the "theory" within the field of educational technology research? *British Journal of Educational Technology, 50*(3), 956–971.
11. Higgins, J. P. T., Thompson, S. G., Deeks, J. J., & Altman, D. G. (2003). Measuring inconsistency in meta-analyses. *BMJ, 327*(7414), 557–560.
12. Holmes, W., Bialik, M., & Fadel, C. (2021). *Artificial intelligence in education: Promises and implications for teaching and learning* (2nd ed.). Center for Curriculum Redesign.
13. Huett, J. B. (2006). The effects of ARCS-based confidence strategies on learner confidence and performance in distance education. *Dissertation Abstracts International Section A: Humanities and Social Sciences, 67*(04), 1237A.

14. Huang, R., Liu, D., Tlili, A., Yang, J., & Wang, H. (2021). Handbook on facilitating flexible learning during educational disruption: The Chinese experience in maintaining undisrupted learning in COVID-19 outbreak. *Smart Learning Institute of Beijing Normal University*.
15. Jensen, L., & Konradsen, F. (2018). A review of the use of virtual reality head-mounted displays in education and training. *Education and Information Technologies, 23*(4), 1515–1529.
16. Keller, J. M. (1987). Development and use of the ARCS model of instructional design. *Journal of Instructional Development, 10*(3), 2–10.
17. Keller, J. M. (2009). *Motivational design for learning and performance: The ARCS model approach*. Springer.
18. Keller, J. M. (2016). *A motivational systems theory of instructional design*. Springer.
19. Lipsey, M. W., & Wilson, D. B. (2001). *Practical meta-analysis*. SAGE Publications.
20. Luckin, R., Holmes, W., Griffiths, M., & Forcier, L. B. (2016). *Intelligence unleashed: An argument for AI in education*. Pearson Education.
21. Milgram, P., & Kishino, F. (1994). A taxonomy of mixed reality visual displays. *IEICE Transactions on Information and Systems, E77-D*(12), 1321–1329.
22. Parong, J., & Mayer, R. E. (2018). Learning science in immersive virtual reality. *Journal of Educational Psychology, 110*(6), 785–797.
23. Pintrich, P. R., & Schunk, D. H. (2002). *Motivation in education: Theory, research, and applications* (2nd ed.). Merrill Prentice Hall.
24. Radianti, J., Majchrzak, T. A., Fromm, J., & Wohlgenannt, I. (2020). A systematic review of immersive virtual reality applications for higher education: Design elements, lessons learned, and research agenda. *Computers & Education, 147*, 103778.
25. Refat, M., Abdel-Aziz, A., & Fathy, A. (2019). Effectiveness of a program based on ARCS model to develop academic research skills. *International Journal of Educational Technology in Higher Education, 16*, Article 13.
26. Russell, S., & Norvig, P. (2016). *Artificial intelligence: A modern approach* (3rd ed.). Pearson Education.
27. Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education – Where are the educators? *International Journal of Educational Technology in Higher Education, 16*(1), 1–27.
28. Zhao, Y., Chen, Y., & Wang, Y. (2022). Review and reflection on the application of ARCS model in online education. *Education and Information Technologies, 27*(1), 97–118.